The Effect of Herding Behavior on Online Review Voting Participation

Emergent Research Forum (ERF) Papers

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Abstract

Online review is an important form of electronic word of mouth (eWOM) that helps customers make purchasing decisions. In a set of reviews, the review with the most helpfulness votes are seen as most helpful. While researchers have demonstrated how review and reviewer characteristics influence helpfulness votes, a largely uninvestigated issue is how herding behaviors can influence customers' voting participation and direction. Drawing on herd behavior literature, we propose that review voters will discount their own information when faced with clear and strong signals from previous voters. Thus, they will herd previous voters' voting direction. On the other hand, review voters will value their own judgments when faced with weak signals from previous voters. Herding can influence both a voter's perception of a review's helpfulness and his/her vote. This research extends review helpfulness literature that herd behaviors could moderates customers' perception of review helpfulness and voting direction.

Keywords

E-commerce, online reviews, customer reviews, product reviews, herding, informational cascades.

Introduction

Online review is an important form of electronic word of mouth (eWOM) that helps customers make purchasing decisions. Seventy-one percent of global online shoppers read online reviews before purchasing a product (The Nielsen Company 2014). Eighty-eight percent of customers trust online reviews as much as personal recommendations (Anderson 2014). A stream of literature focuses on the antecedents that predict online review helpfulness (Baek et al. 2012; Mudambi and Schuff 2010; Weathers et al. 2015; Yin et al. 2014). Current studies show that review metric (Baek et al. 2012; Ghose and Ipeirotis 2011; Hu et al. 2014), review content (Salehan and Kim 2016; Yin et al. 2014), and product type (Mudambi and Schuff 2010; Weathers et al. 2015; Willemsen et al. 2011) together determine whether an online review is helpful or not.

The customers' reasons for perceiving reviews as helpful and casting votes on reviews are due to vividness. The vividness of review attributes attracts customers' attention to cast votes on a review (Kuan et al. 2015). The accessibility and diagnosticity of review attributes are perceived as more helpful to facilitate customer purchasing decisions. However, to our knowledge, little research has been done to distinguish whether customers perceive the reviews as helpful or they just simply herd previous individuals' behaviors. Retail websites help customers identify the most helpful reviews by ranking the orders of existing reviews from most helpful to least helpful. Consumers are in a state of uncertainty, able to see the numbers of previous votes, yet unable to ascertain the reasons behind those decisions. These conditions match preconditions of herd behavior, which include being able to observe previous decisions without explanation and/or being certain (Bikhchandani et al. 1992). If prominent, herding can adversely impact review sets, as more objectively helpful reviews can be underrepresented. In this study, we aim to examine how herd behavior influences customers' voting participation. To bridge this research gap, and extend the literature on herd behavior and online reviews, we formally propose the following research questions:

How does herd behavior moderate the effects of review attributes on i) review helpfulness and ii) voting participation?

Theoretical Development and Hypotheses

The Effects of Review Attributes on Voting Participation

We propose our conceptual model (Figure 1) from the decision-making perspective by incorporating customers' herd behaviors. Customers first evaluate perceived review helpfulness, and then make a decision on whether to cast a (either positive or negative) vote on the review. When evaluating review helpfulness, review attributes, and herd behavior together make a review helpful. Specifically, when the signal is strong, the effect of review attributes on review helpfulness is attenuated due to the presence of customers' herding effect. Customers evaluate review helpfulness accordingly to signal valence by discounting their own information. However, when the signal is weak, customers rely more on their own opinion to evaluate review helpfulness. Therefore, review attributes are the main drivers to predict review helpfulness.

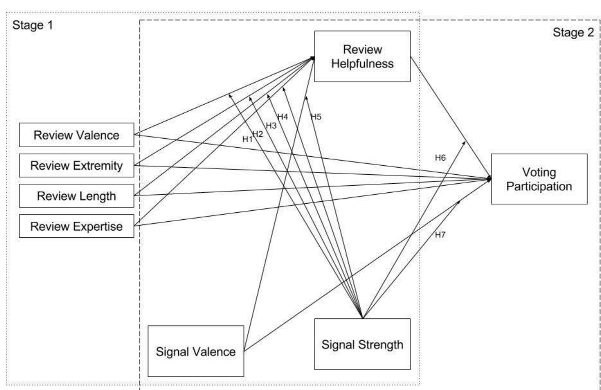

Figure 1. Conceptual Model

Customers cast positive or negative votes on a review to evaluate whether they perceive the review as helpful. The more positive votes a review receives, the more helpful it will be. Sometimes customers will not cast votes on a review, even if customers perceive a review as helpful (or not helpful). *Voting participation* refers to whether a customer casts a vote on a review, and if one does, whether it is a positive or negative vote. Kuan and his colleagues (2015) proposed a vividness-attention framework: given a large number of online reviews, a review must be attended to, in the first place, to be comprehended. A vivid review attracts customers' attention to vote. The reason a review receives votes is due to the eye catching features of a review. For *review valence*, which refers to whether the review provides a positive or negative evaluation of the product (Sen and Lerman 2007), negative information cue is more salient and vivid than positive information, thus, more likely to be attended to. In the context of online consumer reviews, with most reviews being positive as four-star or five-star reviews (Hu et al. 2009), negative reviews are visually more salient and attract more attention. Hence, negative reviews are more likely to be voted than positive reviews.

Review extremity is the extent to which a review is atypically positive or negative (Weathers et al. 2015). Extreme reviews are more likely to attract greater attention (Cao et al. 2011). Furthermore, extreme reviews create cognitive dissonance, a psychological tension that induces motivation to attend to the review (Cooper 2007; Festinger 1957). For example, most customers provide mild positive reviews. An extreme positive or negative review is in congruence with the customer's personal evaluations, creating cognitive dissonance. Hence, extreme reviews are more vivid, and more likely to be voted.

Review length refers to the number of words contained in an online product review. It also reflects the size of a review on the screen. Without having to comprehend the content, a longer review is visually more salient and less likely to be overlooked on the screen than a shorter review. Thus, longer reviews are easier to notice and more likely to have votes.

A review writer's expertise reflects the person's credibility. *Review Expertise* refers to the extent to which the reviewer is a source of valid assertions (Weathers et al. 2015). In Walmart.com and other websites, reviews written by expert reviewers are visually tagged with "TOP REVIEWER" badges, which is an information cue that helps consumers skim through the large volume of reviews to avoid information overload, and heuristically determine which reviews to attend further (Baek et al. 2012; Jones et al. 2004; Yang et al. 2003). Hence, reviews written by labeled expert reviewers are more vivid, thus, more likely to be voted.

Some customers are more likely to participate voting due to the heterogeneity among customers. *Altruism* is the degree to which consumers are willing to improve the welfare of other consumers at a cost to themselves (Rushton et al. 1981). According to social identity theory, customers tend to cast votes on reviews to help other customers to make purchase decisions altruistically (Tajfel and Turner 1979). *Autonomy* is the degree to which consumers feel effective in one's efforts and capable of achieving desired outcomes (Tsai and Pai 2014). Self-determination theory shows that customers are self-motivated to participate the voting process (Deci and Ryan 2000). Thus, we use altruism and autonomy as control variables to partial out the heterogeneity effects among customers.

The Effect of Herd Behavior on Review Helpfulness and Voting Participation

Herd behavior is defined as individuals duplicating their predecessors' choices, while discounting their own information (Banerjee 1992). Therefore, to qualify as herd behavior, two conditions must be met: imitating others and discounting one's own information (Banerjee 1992; Bikhchandani et al. 1992; Sun 2013). The primary driving force behind herd behavior is information cascade (Bikhchandani and Sharma 2000). Information cascade theory describes a process in which a sequence of individuals makes decisions with incomplete and asymmetric information. Individuals' information is private and inaccurate. They observe their own information and their predecessors' actions/decisions, but they are not able to observe the reasons behind those decisions. Given their imperfect knowledge, sequential decision makers infer the actions of their predecessors as an informative signal. This is considered in combination with their private information. As soon as the perceived signal becomes even slightly more informative than private information, individuals tend to defer to the actions of their predecessors and a cascade begins. This leads more people to join the herd. In fact, the probability that a cascade starts after the first few individuals is very high (Bikhchandani and Sharma 2000). Once a cascade starts, the signal of prior decisions could be so strong that the predecessors are imitated regardless of future voters' private information (Anderson and Holt 1997; Bikhchandani et al. 1992; Duan et al. 2009). This sequence describes key drivers and assumptions of information cascade.

Prior research has identified two key drivers: (i) uncertainty about one's own decision and (ii) the ability to observe others' actions (Bikhchandani and Sharma 2000), and four assumptions: (i) actions are sequential, (ii) decision makers combine their private information signals with those of previous individuals, (iii) decision makers act on the basis of observation of actions rather than verbal communication, and (iv) sanctions and externalities that might enforce uniformity are absent (Bikhchandani et al. 1992), for the process of information cascade. The voting system of online reviews satisfies each of the four assumptions mentioned above. First, consumers view the product descriptions and reviews at their leisure. One can reason that the votes are not acquired simultaneously, but in a sequential fashion. Second, the number of positive votes and total votes are displayed for each review as an identification of signals by previous individuals, but the reviews are available for consumers to read. Therefore, consumers could easily combine their private information signals with those of previous individuals. Third, when voting on a review, one does not have access to reasoning for each of those votes. Since voters are anonymous, there is no way for them to communicate with each other. Fourth, no forces are present to promote consumers to vote similarly or differently than their peers. Furthermore, informational cascades could be particularly prominent on the Internet due to the massive amount of online consumer reviews, causing information overload, making it difficult for consumers to choose reliable reviews (Baek et al. 2012).

Review attributes are not the only information customers can access on websites. Amazon, for example, also provides how many people found the review as helpful so far. For example, "90 out of 100 people found this (review) helpful", this is a signal indicating other customers' combined evaluation of review helpfulness without knowing their decision-making process. A customer will combine review signal with his or her own evaluation on review helpfulness to make the final decision due to information overload. The signal, for example "90 out of 100 people found this (review) helpful", actually provides two dimensions of information cues: signal strength and signal valence. *Signal strength* in this context refers to a customer's observation of how many previous customers voted on a review. The more customers that vote on a review, the stronger the signal is. *Signal valence* refers to whether previous customers sent out a positive or negative signal by casting votes on a review. In our example, 90 percent of previous customers think the review is helpful. Thus, this is a positive signal valence. When a customer is exposed to a strong signal, the customer is more likely to discount his own review helpfulness evaluation, and herd, following the majority's opinion (Sun 2013). Therefore, a customer's helpfulness evaluation of a review is more likely to be consistent with signal valence. Furthermore, the effect of review attributes on review helpfulness will be attenuated. However, when a customer is exposed to a weak signal, the customer is less likely to herd other people's decisions, and more likely to insist his/her own opinion. Thus, review attributes are the main drivers to influence the evaluation of review helpfulness. Therefore, we form hypotheses 1 to 5 below:

H1-4: When signal strength is strong, the effect of review valence (H1), review extremity (H2), review length (H3), review expertise (H4) on review helpfulness is weaker than when signal strength is weak.

H5: When signal strength is strong, the effect of signal valence on review helpfulness is stronger than when signal strength is weak.

Customers' voting participation depends on review helpfulness and herd behavior. When customers decide to vote, the positive or negative vote depends on signal strength and signal valence of a review. When the signal is strong, customers' voting participation is consistent with signal valence of the review. However, when the signal is weak, customers' voting participation would be consistent with review helpfulness. Therefore, we propose hypotheses 6 and 7 below:

H6: When signal strength is strong, the effect of review helpfulness on voting participation is weaker than when signal strength is weak.

H7: When signal strength is strong, the effect of signal valence on voting participation is stronger than when signal strength is weak.

Method

The first study will analyze a large sample of customer reviews collect from Walmart.com. Since we cannot capture a customer's decision to not vote on a review, in our empirical study, we will consider voting participation from the aspect of voting direction: to examine whether customers cast positive or negative votes on a review. We will fit our data using a Poisson model. The second study follows up with an experiment. Each of the 100 participants will be randomly assigned to two of six products. First, we will establish an online review context for them by introducing three online reviews for each product. Then, they will read one real review captured from Walmart.com. They will evaluate each review by assessing its review helpfulness, voting participation (vote up, down, or not vote). The participants repeated the process for each of the other product. A generalized least square based seemingly unrelated regression (GLS-SUR) will be used to analyze the data. All measures will be adopted from existing instruments published in IS literature. We will present our results during the conference presentation in Boston.

Discussion

Going beyond extant studies, we expect to find that herd behavior plays different roles in review helpfulness and voting participation. These relationships receive little attention from researchers. Unwarranted votes can cause sub-optimal reviews to rank higher and dominate customers' attentions. These models could help retailers in designing a review system that can tease out the effects of herding.

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